THE DEVELOPMENT OF IOT NETWORK DEVICE FOR THE DETECTION OF ATLANTIC CROAKER FISH USING MODIFIED YOLOv8

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Abstract

Detection of Atlantic croaker fish within the marine environment is a major problem in the field of aquaculture. This is due to the nature of aquatic habitat, where temperature, pH and salinity of water have an adverse effect on the availability of aquatic animals in the ecosystem. Traditional methods of detection of the Atlantic croaker (*Micropogonias undulatus*) fish typically involve a combination of local knowledge, observational techniques, and acoustic cues which are often limited in terms of accuracy and precision. Inaccurate detection has an adverse effect on business models, consumers behavior and prediction of the availability of the croaker fish as requested by consumers. To mitigate this effect, an Internet of Things (IoT) Network device was developed

using an Espress if 32-bit Microcontroller (ESP-32), OV7476 camera sensory Modules integrated together with a programmable ESP-32 device to capture images of various objects in the marine environment. The captured images were transferred real time into the cloud for Data Preprocessing.

A Modified You Only Look Once version 8 (M-YOLOv8) object detection algorithm was developed to analyze and detect the presence of the Atlantic croaker fish. The 2cf in the backbone layer of a YOLOv8 Architecture was replaced with a Residual Network (RESNET). Experimental results showed that the system achieves an accuracy 94.6%, precision of 91.8%, Recall 92.3%, F-1 score of 92.7% and mean Average Precision (mAP), of 93.9%. This shows a remarkable achievement in the detection and prediction of the availability of the Atlantic croaker fish in the marine environment, when compared to the single short Detection and the Region-based Convolution Neural Network Detection Algorithm Model

Keyword: Atlantic croaker fish, ESP 32 Microcontroller, M-YOLOv8, YOLOv8, Region based Neural Network (R-CNN) and single short detector (SSD)

1.0: INTRODUCTION

The monitoring and preservation of aquatic lives in the Eco system have become increasingly important due to the growing environmental impacts of climate change, overfishing, and pollution (Kim et al, 2025). Fish species like the Atlantic croaker, known for their ecological and commercial value, play a vital role in maintaining the balance of marine ecosystems (Han et al.2020). Traditional fish monitoring methods such as manual surveys, trawling, and acoustic tagging are often invasive, labor-intensive, and lack real-time responsiveness. As a result, there is a rising demand for intelligent, automated systems capable of real-time fish detection and monitoring in underwater environments (Chen et al. 2021).

Underwater Wireless Sensor Networks (UWSN) have emerged as a transformative technology for environmental monitoring, offering distributed sensing capabilities across vast underwater areas. These networks consist of interconnected sensor nodes equipped with cameras, hydrophones, and other sensing devices capable of collecting and transmitting data in real time (Zhao et al.2021). However, underwater environments pose significant challenges to visual detection systems, including poor lighting conditions, turbidity, low contrast, and signal attenuation. These conditions drastically reduce the accuracy of conventional object detection algorithms when applied directly. To address these challenges, this research integrates a modified You Only look once Object detection algorithm (M-YOLOv8) deep learning model with a UWSN framework to enable accurate and real-time detection of croaker fish. YOLOv8, is an object detection model, which is known for its speed and precision in the detection of object, but its performance degrades in low-quality underwater imagery (Zhang et al. 2023). Therefore, we propose a reformed version of YOLOv8, enhanced with underwater-specific preprocessing, optimized training on annotated croaker fish datasets, and architecture modifications for improved robustness under aquatic conditions.

The Modified Yolov8 (M-Yolov8) with the internet of Things (IoT) is able to detect croaker fish with high accuracy in underwater environments. The developed model performance was evaluated in terms of detection accuracy, communication efficiency and real-time applicability. By combining advancements in wireless sensor technology and deep learning-based computer vision, this research provides a scalable, affordable and a low-latency solution for autonomous marine life monitoring. The proposed system has potential applications in marine biology research, sustainable fisheries, habitat assessment, ecological data collection. Computer vision and aquaculture.

2.0: ATLANTIC CROAKER (*Micropogonias undulatus*)

The Atlantic croaker (*Micropogonias undulatus*), known regionally as croaker, hardhead, golden croaker, or Granier, is a marine fish belonging to the drum family, Sciaenidae. As with other species in the drum family. It was named for the croaking noise it produces by oscillating the muscles around its distended swim bladder (Anderson et al). The species is a widely consumed saltwater fish found along the Atlantic coast of North America, from Massachusetts to Florida, and into the Gulf of Mexico. It is a robust fish that can withstand various temperatures and salinities and adapts well to captivity. It possesses a body that is fusiform (spindle-shaped) and moderately compressed laterally. The colours of croakers can vary from lackluster silver to golden yellow and copper-bronze. Their backs are dark, and their sides have black spots that create uneven, sinuous patterns (valenza et al.2025). Limited Shifts in Sulfur Stable. The gill cover of croakers features three to five notable spines, and there are usually three to five chin barbels located beneath a sub-terminal or slightly downward-angled mouth. The lateral line reaches the end of the caudal fin, which has a slight convexity. The body is fusiform (spindle-shaped) and moderately compressed laterally. The colors of croakers can vary from lackluster silver to golden yellow and copper-bronze (Mares, 2025). Seasonal changes in gene expression of the three estrogen receptor subtypes in the Atlantic croaker,. Their backs are dark, and their sides have black spots that create uneven, sinuous patterns.

They can grow quickly in the They live for two to four years and can develop rapidly in the wild. Juveniles in the Gulf of Mexico's estuarine nursery areas gain more than 0.43 ounces (12.3 g) and 1.4 inches (3.5 cm) of length every month. There is little information available on the growth rates of wild adults because these rates are strongly impacted by latitude and the corresponding variations in mean water temperature. Although 16 inches (40.6 cm) and 2 pounds (0.9 kg) are considered the maximum growth target for cultivated Atlantic croaker food fish, several specimens obtained in the wild have grown larger than these measurements. Croakers can grow up to 29 inches (736.6 mm) in length and 8.69 pounds (3.94 kg) in weight, according to current state angling records.

Atlantic croakers from wild catch are exported to other countries from time to time, but this practice has diminished due to the reduction of commercial landings in the last few years. (whaley et al, 2025). Establishing controlled production of Atlantic croaker could create a consistent supply, offer size-specific bait grades, reduce pressure on wild populations, diversify aquaculture operations, and aid in food fish sales (Valenza et al.2025). The picture of the croaker fish in the Gulf of Mexico waters is shown in Figure 1.

Figure 1: The Atlantic croaker fish

Source: Valenza et al. 2025

Atlantic croakers are often seen in shallow coastal waters (estuaries, bays, and nearshore zones). basically, found over sandy or muddy bottoms. The Juveniles migrate into estuaries and rivers (Boyle et al,2025). Their average size is between 6 to 12 inches. Although, they can reach up to 24 inches and weigh a couple of pounds. Physically, they appear silvery-bronze body and irregular wavy lines on their back and they have a Pointed snout, with barbels (whisker-like feelers) under the chin. They often feed on Benthic feeders (feed on or near the bottom), worms, crustaceans, small fish, and detritus. (Boyle et al. 2025)

3.0: Traditional means of identification Atlantic Croaker Fish

Monitoring and detecting Atlantic Croaker (Micropogonias undulatus) populations have historically relied on a range of manual and semi-automated methods. While these techniques have contributed significantly to fisheries research and management, they are often

limited in terms of spatial coverage, efficiency, and species-specific accuracy (Jiang et al, 2025)

One of the most common traditional approaches for detecting and estimating croaker populations involves the use of bottom trawls, gill nets, and seine nets. These methods physically capture fish and allow researchers to identify species and measure biomass and population density. It records the biological data including the length, weight, age, etc. Of the fish. However, it has some limitations which is labor-intensive and time-consuming

(Shao et al. 2023). It can be invasive or destructive to non-target species and habitats. In addition, it has limited spatial and temporal coverage (point-in-time data collection). It also requires expert handling for accurate species identification.

Another traditional method is the use of the Hydroacoustic. These methods use sound waves to detect fish presence and estimate abundance. This method involves sending acoustic pulses into the water and interpreting echoes reflected by fish or other underwater objects. This method ca detects vertical and horizontal distribution patterns for the identification of the croaker fish. Although, this method can not reliably differentiate between species without complementary methods (e.g., net validation). And the performance of this method is often affected by background noise and seafloor interference, especially in shallow coastal or estuarine environments where croakers are commonly found. besides, it requires complex post-processing and trained personnel. since Atlantic Croakers produce characteristic “croaking” sounds during spawning seasons using their swim bladders, Passive Acoustic Monitoring (PAM) has been explored for species-specific detection. It has various advantages and disadvantages This method is non-invasive and continuous and it also allows temporal monitoring of spawning activities. It is also useful for identifying presence and behaviour of fishes in the marine environment. However, this method is only effective only during specific life stages (e.g., spawning season).it also requires specialized equipment (hydrophones) and advanced signal

processing. Besides, sound signals can be masked by ambient underwater noise (e.g., boats, waves), thereby giving a false or error detection.

Visual Observation is used by fishermen and aqua culturist to identify the presence of the croaker fish in a clear and shallow waters. They also use the scuba diving for direct observation and a Remotely Operated Vehicles (ROVs) equipped with cameras. However, this observation technique is limited by visibility, lighting, and water turbidity. Also, it is not feasible for large-scale or long-term monitoring. It is also prone to Human error and subjectivity can affect species identification.

Other methods of traditional means of identification include the “Listening for the "Croak" sound, reliance on experience with local water patterns and watching for bird activities. Croaker fish get their name from the croaking or drumming sound males produce using their swim bladders, especially during spawning season. In quiet, shallow waters, especially at night, experienced fishers could hear the croaking sounds, helping them locate schools. This method was mostly used during spawning months (late summer to fall) when croaking is loudest.

Furthermore, traditional fisherfolks often relied on experience with local water patterns, such as depth (croakers are often found in shallow coastal waters, estuaries, and bays), tides (croakers feed more actively during incoming and outgoing tides when food is stirred up), bottom type (Preferred areas include muddy or sandy bottoms, which are good for foraging benthic organisms). Although, this method achieves a measure of identification, it can not be relied upon because of its error rate. Fisherfolks also observed diving or feeding birds (like gulls or pelicans) which often signaled the presence of baitfish and by extension, predators like croakers nearby. Though croakers aren't surface hunters, their activity might disturb baitfish, attracting birds.

Additionally, croakers follow predictable seasonal migrations.
During summer season, they move inshore to estuaries to feed and grow. However, during Fall/Winter season, they migrate offshore to spawn. Also, Local fishers traditionally knew the best months and locations to

target croakers based on this cycle. Fishers would also use live or fresh natural bait like the Shrimp, Bloodworms and Cut fish. When croakers were active, bait would get bites quickly, signalling their presence. If there were no bites in 10–15 minutes, the fisher would move to another spot.

Moreover, in regions where small canoes, skiffs, or paddleboats were used, fishers would: Drift over known hot spots. Use hand lines or simple rods. Detect croakers through repeated testing of certain locations. Elders and seasoned fishers passed down: Specific "croaker holes" (reliable fishing spots). changes in the weather, wind, or moon indicating croaker activity. For instance, “when the croakers start croaking, the shrimp are running" sayings like this helped connect multiple ecological cues. These traditional methods reflect a deep connection with the marine environment and highlight the ecological knowledge held by coastal fishing communities (Shao et al, 2023)

5.0: RELATED WORKS

The detection and monitoring of marine life, particularly fish species such as croaker fish, have gained significant attention due to their ecological and economic importance. Traditional methods for underwater fish detection largely relied on manual observation and sonar technology, which can be labor-intensive and sometimes ineffective in complex marine environments. In recent years, the advancement of Underwater Wireless Sensor Networks (UWSNs) has revolutionized marine monitoring systems. The UWSNs enable real-time data collection and transmission from submerged sensors, allowing continuous monitoring of underwater environments. Research by Akyildiz et al. (2005) laid foundational work on the challenges and architectures of underwater wireless communication, highlighting the potential for environmental monitoring applications. Concurrently, computer vision techniques, particularly those based on deep learning, have demonstrated remarkable progress in image-based object detection tasks. The You Only Look Once (YOLO) series of algorithms, including YOLOv8, are state-of-

the-art object detectors known for their speed and accuracy. Studies such as Redmon et al. (2016) introduced YOLO as a real-time detection framework, while more recent works have enhanced its architecture to handle complex and noisy visual data. In underwater environments, the challenges of varying lighting conditions, turbidity, and visual distortion make object detection notably difficult. To address these, researchers have employed data augmentation strategies and domain-specific model adaptations.

Singh et al. (2022) proposed synthetic data augmentation techniques simulating underwater conditions to improve model robustness. Similarly, refined versions of YOLO have been adapted for underwater imagery, optimizing feature extraction and reducing false positives.

Integrating UWSNs with advanced computer vision models like a modified YOLOv8 presents a promising approach for effective croaker fish detection in marine settings. This integration not only facilitates automated and continuous monitoring but also leverages real-time data transmission capabilities for timely ecological assessments. Despite the advancements, challenges such as energy efficiency of underwater sensors, communication reliability, and model generalization across different underwater environments remain open research areas. This study aims to build upon existing literature by proposing a novel framework combining UWSNs with an improved YOLOv8 model tailored for underwater fish detection, specifically targeting the croaker fish in marine ecosystems.

Ma et al. (2023) used a modified YOLOv5 for underwater fish detection and proposed a data augmentation strategy to simulate underwater lighting and turbidity conditions, improving robustness in harsh environments. To address issues such as varying lighting conditions and turbidity, they proposed a novel data augmentation strategy that synthetically simulates these environmental factors. This approach led to improved detection robustness in visually degraded and complex

underwater scenes, demonstrating its effectiveness in real-world scenarios.

Multi-Scale Adaptive Robotics Vision (MARS) stands out as a significant advancement in the field of underwater robotic vision. The MARS combines Residual Attention YOLOv3 with Domain-Adaptive Multi-Scale Attention (DAMSA), improving detection precision and adaptability in various underwater situations. MARS notably attains a mean Average Precision (mAP) of 58.57% on the original dataset, showcasing its ability to detect crucial underwater objects. Its strong performance is underscored by a mAP of 36.16% on the augmented dataset, demonstrating adaptability across different conditions. To tackle issues concerning the detection of underwater targets, an enhanced version of the You only look once version 7 was suggested. This network incorporates innovations like the ACmix Block module, ResNet-ACmix module, and Global Attention Mechanism (GAM), leading to improved feature extraction and faster network reasoning. The enhanced YOLOv7 network exceeds the performance of both the original YOLOv7 model and other widely used underwater target detection techniques, with mean average precision (mAP) values of 89.6% on the URPC dataset and 97.4% on the Brackish dataset. A combination of max-RGB and shades of gray methods was first used by Han et al. (2020) to enhance underwater images. A Deep convolutional neural network approach was then employed for recognizing underwater targets, yielding favorable outcomes.

Underwater environments pose significant challenges for computer vision applications due to poor visibility, color distortion, scattering, and light absorption. These factors degrade image quality and reduce the accuracy of object detection models. To address these challenges, Han et al. (2020) proposed an underwater image processing and object detection framework based on deep convolutional neural networks (CNNs). Their method integrated image enhancement techniques—such as color correction and contrast adjustment—with a deep CNN model tailored for underwater object detection. Experimental results

demonstrated that preprocessing significantly improved the detection accuracy in complex underwater scenes, particularly in conditions with severe turbidity and low lighting. This work highlights the importance of customized preprocessing pipelines in underwater computer vision and sets a precedent for integrating image enhancement with deep learning to improve detection performance. The study provides a strong foundation for the use of reformed object detectors, such as YOLOv8, which could benefit from similar preprocessing when applied to underwater tasks like croaker fish detection in wireless sensor network-assisted systems

Chen et al. (2021) introduced an improved version of the YOLOv4 neural network tailored for underwater target recognition. Their enhancements included optimized anchor box generation, attention mechanisms, and a modified backbone network for better feature extraction. These improvements significantly boosted detection precision and recall rates in complex underwater scenes. The study reinforced that off-the-shelf YOLO models require architectural adaptations to perform effectively under water, where standard training data and assumptions often do not apply. Expanding on the theme of lightweight and efficient underwater detection, Zhao et al. (2022) introduced a modified YOLOv4-based architecture incorporating deformable convolution. Their model was specifically designed for detecting dead fish in aquatic environments, a task requiring high sensitivity and real-time processing. By using deformable convolutional layers, the model was able to better adapt to irregular object shapes and variable orientations in water. Importantly, Zhao et al. emphasized lightweight model design, making their approach suitable for deployment on edge devices or resource-constrained systems —such as those found in Underwater Wireless Sensor Networks (UWSNs).

Sun and Xu (2023) explored large kernel convolutions within the YOLO framework for ship detection in marine surveillance video. Their approach addressed a key limitation of conventional small-kernel CNNs including restricted receptive fields that fail to capture long-range

contextual information. By incorporating large kernel convolutions, the model achieved superior performance in detecting objects with vague boundaries or large-scale structures, a characteristic challenge of marine environments. Although their application focused on ships, the method demonstrates strong potential for improving detection in underwater imagery, where fish and other marine organisms often appear partially occluded, camouflaged, or distorted due to turbidity.

Zhang et al. (2023) introduced YOLO-SWFormer, a hybrid architecture combining YOLO detection with Shifted Window Transformer (Swin Transformer) modules. This model was designed for detecting marine targets in Plan Position Indicator (PPI) images, which, like underwater visuals, contain significant clutter and abstract patterns. The integration of transformer-based attention enabled the model to better understand long-range dependencies and spatial relationships, outperforming traditional CNN-based models in complex detection scenarios.

Shen et al. (2023) introduced a criss-cross global interaction-based selective attention mechanism into the YOLO architecture, specifically for underwater object detection. Their method allows the model to dynamically focus on globally relevant features by modeling long-range dependencies along both horizontal and vertical axes. This significantly improves detection performance in cluttered and noisy underwater environments, where conventional convolutional layers struggle to capture salient patterns. Their results underscore the importance of global spatial reasoning in deep learning models tailored to underwater vision.

Yu et al. (2023) proposed an efficient detection method for deep-sea netting breakage, which combines attention mechanisms with enhanced receptive field feature extraction. Their model is designed for scenarios where visual input is both sparse and highly degraded conditions similar to those encountered in croaker fish detection in deep marine environments. The model's emphasis on spatial feature enhancement and computational efficiency makes it particularly relevant for real-time applications on embedded or low-power platforms.

Lv et al. (2022) focused on detecting attached marine organisms using convolutional neural networks, tackling the problem of recognizing small, camouflaged, or irregularly shaped aquatic lifeforms affixed to underwater structures. Their methodology underscores the necessity of adapting CNN architectures and training strategies to the unique visual characteristics of marine biofouling and related phenomena, offering insights potentially transferable to croaker fish detection, especially when fish behaviour involves substrate interaction.

Li et al. (2022) enhanced YOLOv5 with triplet attention and optimized prediction heads specifically for deployment on underwater mobile platforms, balancing the need for precision and computational efficiency in dynamic underwater monitoring. However,

Li, Shi, and Jiang (2023) specifically proposed an improved YOLOv5 model for fish detection, tailoring the architecture to better handle underwater fish appearance and behaviour. Their improvements include refined feature extraction and optimized detection heads, demonstrating significant gains in accuracy and robustness.

Yu et al. (2023) introduced Inception NeX, a novel convolutional architecture that combines the strengths of Inception modules with the modern Conv NeX design. This hybrid approach leverages multi-scale feature extraction alongside the efficiency and simplicity of ConvNeXt, leading to improved representation learning and performance in computer vision tasks. Although not directly applied to underwater detection, InceptionNeXt's architectural innovations offer promising directions for enhancing feature extraction in underwater object detectors, especially where multi-scale and contextual understanding are critical due to varying object sizes and challenging visual conditions. Integrating such state-of-the-art backbone designs with YOLO frameworks could provide additional improvements in accuracy and robustness for croaker fish detection in marine environments.

6.0 APPLICATION OF THE UNDER-WATER WIRELESS SENSORY NETWORK

The application of wireless sensor network can be in various fields which include but not limited to oil exploration, marine surveillance, aquaculture, fishery management, military, water Engineering, ship wreck and management, water management and to study plant in waters. However, the deployment of this wireless sensor has been restricted due to certain challenges especially in Africa where there is abundance of water bodies.

The marine world contains of various aquatic fishes, and marine animals which serves either as a source of income, research study, or tourist for various individuals and research hers. Example of such development is the underwater wireless sensory device. One of such is the sensor network. The sensor is a device that responds to any form of input from the environment (Lind et al., 2022). Increase in human population has led to change in climatic condition, weather condition, and change of lifestyle and gradual declination of aquatic animals (Abbass et al., 2022; Dirzo et al., 2022). These changes have led to change in water currents, water pollution, water waves, change in aquatic world and other effects which are feasible in the life pattern and adaptability of aquatic animals (Relyea, 2018). In addition, gradual change to habitat as a result of pollution and contamination is a major challenge to the aquatic animals which makes this aquatic animal to tend towards extinction (Lind et al., 2022; Brotherton et al., 2020, Habibullahetal.,2022).

Traditional means of Sensory network uses cable for communication and transmission of data. However, because of the cost of deployment and limitation of this method, the wireless sensory network is introduced to overcome these limitations, because the USWNs perform much better than the cable communication

In adequate wireless sensors for detection of aquatic animals before they go into extinction is a very important issue that needs urgent attention. Sensors are used in agriculture, marine technology, surveillance, oil monitoring and theft, sea monitoring. Sea archelogy, data centers, meteorology, heating, mining industry, aviation, ventilation, sub marine and also in domestic activities (Habibullah et al. 2022). The

USWNs consist of autonomous vehicles and sensors that are deployed in a particular area to perform monitoring and data collection tasks. The UWSNs are usually affected by various factors which has limited its deployment. Factors including cost, areas of deployment, type of sensors to be deployed, configuration of sensors, battery or energy level of such and several factors. Other factors that affect underwater wireless sensory network can be categorized into physical, biological and chemical component of water. These affects the performance of water and sensors with respect to the identification of aquatic animals under the water environment (Sendra et al., 2023).

Underwater wireless communication is an evolving technology which involves lots of techniques and hardware to software. The architecture involves, radio frequency, magneto- inductive communication, optical Communication, acoustic communication, and cable communication. Since the medium of deployment is water- various water attributes and composition are considered in order to improve the performance of the UWSNs. Research as shown that the area of deployment has an extensive impact and effect on the performance of USWNs. In Africa- Nigeria precisely, the movement of the Atlantic Ocean has shown to be horizontal with high water waves and water current. The salinity and oxygen tend to be different from that of Europe and other continent. Underwater Sensor Networks face challenges like cost of deployment, limited bandwidth, high propagation delay, 3-dimensional topology, power constraints and others. The USWNs are often used by marine engineers, oceanographers, scientist because of its enormous advantage in the marine environment. It comprises of Autonomous Underwater vehicle otherwise referred to as unmanned water vehicle, sensors, camera, battery, and other components. In this study, various challenges were considered that is been experienced in the deployment of UWSNs. Trade off were also considered in the development. The installation, configuration and deployment of various hardware and software to identify images and objects under the waters has faced various challenges. These challenges are due to the variations of water composition, which include the physical, chemical and biological composition of water. Besides, the

nature of the body of water also varies with environment and composition of the water bodies. The kind of animals and species of aquatic animals living under the water is also another factor that makes identification of such difficult. Smart wireless sensor network can solve the problem of identifying objects and images in the terrestrial under water environment. The traditional means of using terrestrial wireless sensory network could not work effectively in under water because of various factors like the water temperature, humidity, salinity, Ph and other underwater factors. In addition, the transmitting ability of Terrestrial wireless sensory network is limited and cannot transmit data from under water to the surface effectively considering the nature of this device. Hence, migration towards the underwater sensory network became necessary and paramount for researchers and scholars to effectively detect objects and images underwaters.

7.0: USES OF USWNs

The UWSN can be used for monitoring of underwater environment (including quality of waters, aquatic lives); identification and detection of objects, evaluation of quantity of food eaten by aquatic animals; evacuate minerals deposited under ocean beds and monitoring of pollution, gas pipelines and cables under water, among others (Lloret, 2013; Felemban et al., 2015; Almutairi and Mahfoudh, 2017; Aldosari et al., 2020;). It has also been used can be used as a means of surveillance to detect unwanted intrusion (Khan et al., 2021; Almutairi and Mahfoudh, 2017, Lloret, 2013, Felemban et al., 2015; Amoli, 2016; Chandrasekhar et al., 2006)

Despite the innovations and discovery – and applications of UWSN, there are lots of challenges facing the development of the UWSN. These challenges include limited Bandwidth, High Propagation delay because sound travels slowly underwater which causes significant latency. Besides, there is a high error Rates & signal distortion signals which are affected by noise, multipath propagation, limited Energy Constraints. This is because sensor nodes are battery-powered and often hard to recharge or replace. (Pachouri et al. 2023, Mahmood et al. 2019).

7.0: METHODOLOGY

DESIGN OF THE IoT- UNDER WATER WIRELESS SENSORY NETWORK

The IoT- Under Water Wireless Sensory Network (IoT-UWSN) is a novel method that involves the integration of various hardware and software together for real time sensing and detection of various aquatic animals in the marine region – Atlantic croaker inclusive. In this research study, an IoT-UWSN was designed using Espress-if 32-bit Micro controller (ESP - 32), OV7476 camera sensor module, Future Technology Development Interface (FTDI 1232) Module, Jumper cables, Universal Serial Bus (USB) interface cable, and Arduino software (for the configuration of the hardware), and the breadboard (for connecting and integrating all the other components).

The ESP-32 Microcontroller was connected to the breadboard for ease of installation. The OV240 camera sensor module was attached to the ESP-32 via brownish film attached to the OV240 camera sensor module. The FTDI1232 module was connected to the ESP-32 camera using four jumper cables for data transfer. Figure 2.0 shows the developmental phase of the IoT-UWSN device for real time capturing of aquatic fishes in the marine environment

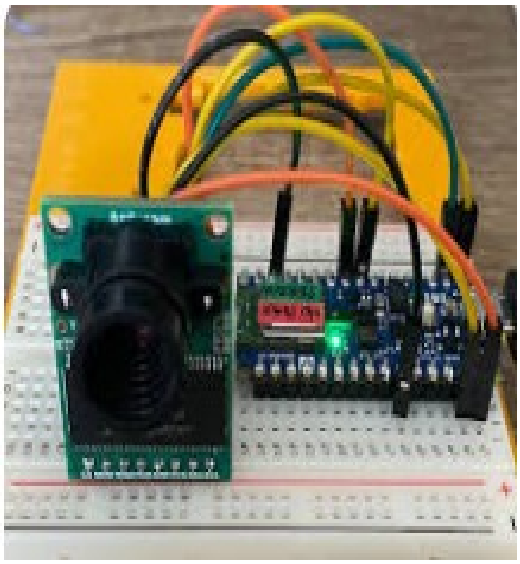

Figure 2.0: Configuration of IoT- UWSN

The developed device was connected to a source of power and suspended in the marine environment for capturing of various images, objects, pictures and videos of aquatic animals, fishes which is used for training and identification of the croaker fish (Figure 3).

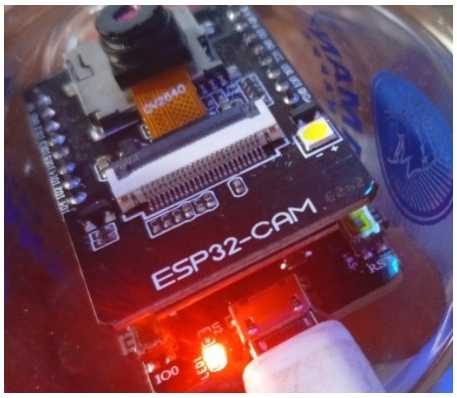

Figure 3.0: Picture of the IoT-UWSN deployed for the detection of marine animals in an underwater environment

Study Area

The IoT-UWSN was installed, configured and deployed at Elegushi beach, in Lekki peninsula, Lagos state, southwest Nigeria. The Lekki Beach is located at approximately 6°24′N and 6°60′N latitude and 2°40′E and 4°20′E longitude. It is a private beach owned by the Eleguishi family of Lagos state. The beach covers about 30 to 45 kilometres, and covers about 45,000,000 SqM^2.The Beach is a recreational centre and tourist centre that attracts people all over the world. This beach was considered because it is an extension of the Atlantic Ocean that flows from Lagos-Nigeria down to other countries. In addition, it contains numerous species of Atlantic croaker fish.()

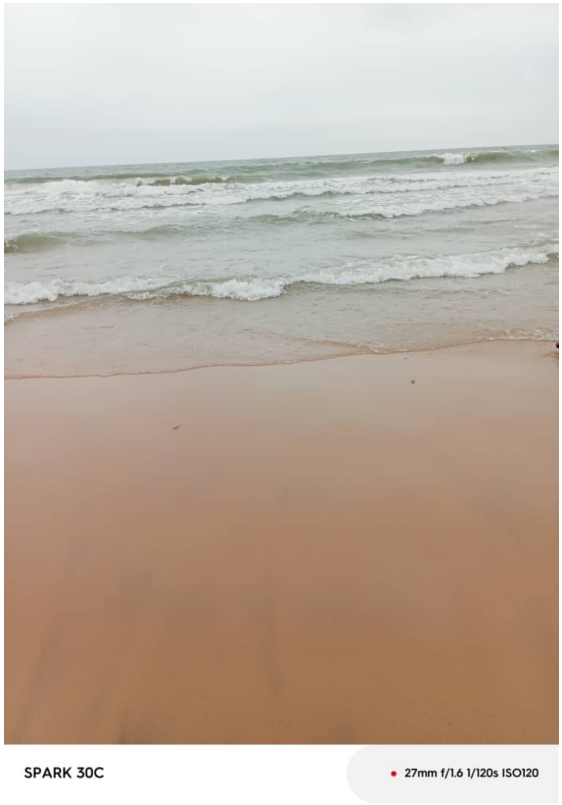

Figure 4.0: Elegusihi beach in Lagos Nigeria where the IoT-UWSN is been deployed under waters to capture images of the croaker fish in a real time.

The developed device was suspended under the water region to capture, record and transmit various images of captured dataset. The IoT-UWSN was deployed in the marine water for a period of seven days. At various intervals, various images of objects in the marine ocean, were captured by the IoT-UWSN and transmitted into a server system positioned outside the marine habitat.

The captured image dataset went through various level and stages of data pre processing, which include data inspection & profiling, data cleaning, data transformation, data integration, data reduction, feature engineering and data splitting. Figure 7 explains the flow of actions of the sequence of activities that takes place during the data analysis of the identification of croaker fish when captured by images of the camera using the IoT-UWSN.

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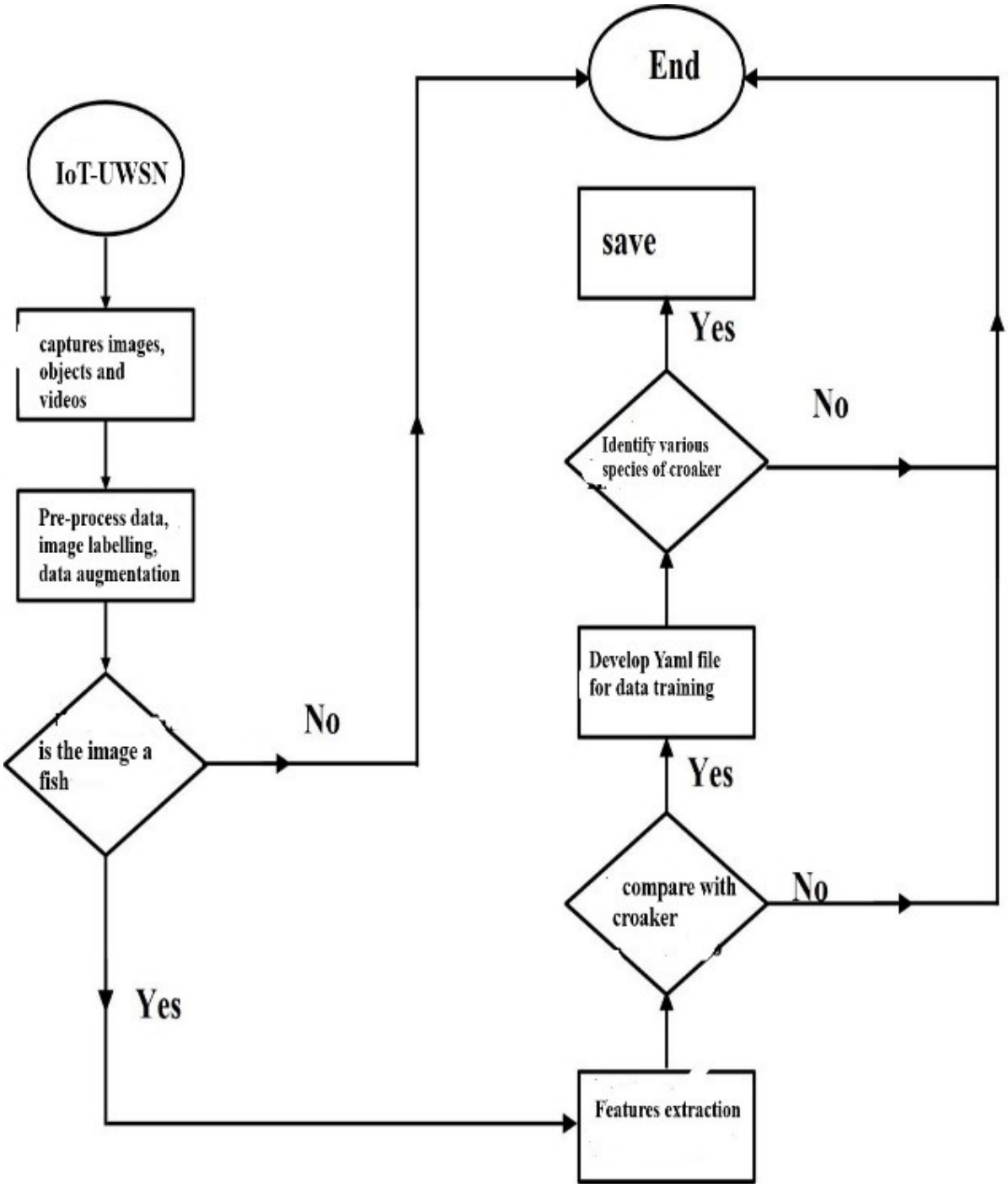

Figure 7.0- flow chart diagram for IoT-UWS

The figure 7.0 above shows the sequence of actions that takes place in the detection of croaker fish by using an Internet of thing under water wireless sensory network device using ESP-32 Micro controller. The IoT-UWSN was suspended in the marine environment to capture various images of objects, images and every thing both static and dynamic in the marine environment. The captured images undergo various methods of data preprocessing and cleaning. Both video and static images were

captured and transferred into a server system outside the marine environment. The video files were converted into frames that was used in the training of the model. Also, the captured images were labelled to give a unique identity. The data was augmented, annotated using ip labelling software and python 3.11. further process includes data classification and segmentation of each of the data set. The dataset was classified based on each of the captured item like tortoise, fish, shrimps etc.

If the item is seen as a fish, the features are extracted using Ip labelling software. The extracted features are used for the training of the dataset using extracted parameters. The Yaml file was created which was used to train the dataset in identifying various species of the croaker fish by inculcating and implementing the YOLOv8 in the detection of the croaker fish.

8.0 MODIFIED YOLOv8 (M-YOLOv8)

YOLOv8 is the latest generation in the YOLO (You Only Look Once) family of real-time object detection models, released by Ultralytics in 2023. It builds upon the strengths of its predecessors with several key improvements aimed at enhancing accuracy, speed, and usability. The Modified YOLOv8 (M-YOLOv8) was developed from the existing YOLOv8. The M-YOLOv8 was modified by replacing the 2cf in the backbone layer with a Residual Network (RESNET), which supports improved feature representation, pretrained weights availability, which has more potential for better accuracy. Further enhancements included image preprocessing, noise filtering, and architecture fine-tuning to improve detection accuracy in underwater settings. These include image preprocessing, noise filtering, and architecture fine-tuning to improve detection accuracy in underwater settings. This supports deeper residual connections and enhance feature extraction Which helps in the detection of intruders with high accuracy. The M-YOLOv8 is an advanced model of the YOLOv8 which is used for the detection of objects with optimal accuracy. After a period of twenty-one (21) days, eighteen thousand seven hundred and thirty-five (18,735) volume of image datasets was captured by the IoT-UWSN device. The image datasets were captured

and transmitted into the cloud. The captured datasets were pre-processed, classified, segmented, detected. It was annotated using the Ip labelling tool. All the identical features were annotated by drawing a bounding

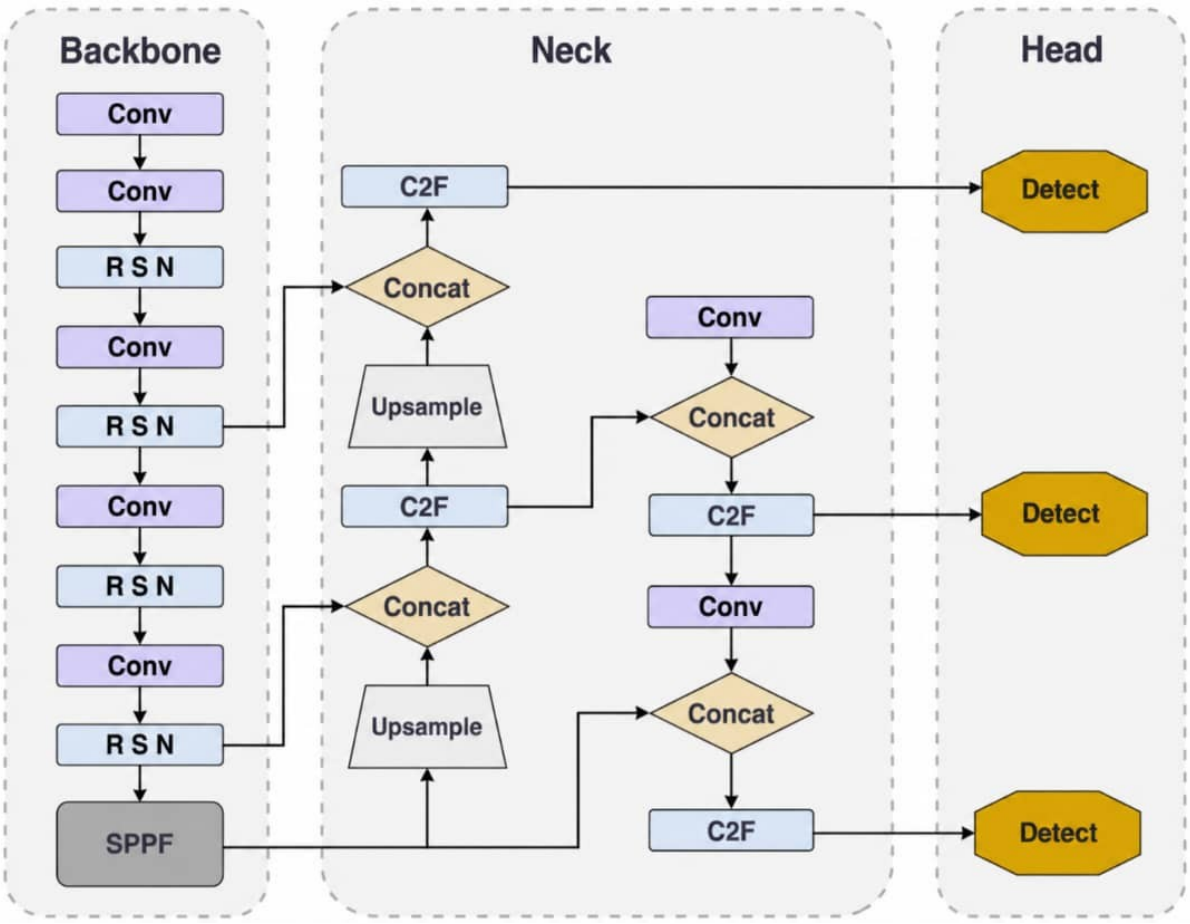

Figure 8.0: M-YOLOv8 Architectural Model.

9.0: RESULTS AND DISCUSSION

The image dataset was trained using the R-YOLOv8, YOLOv8, Region based convolution neural network (R-CNN) and the single short detection algorithm (SSD), in order to evaluate the accuracy of the developed model.

The result was generated and using the standard metrics: precision, recall, F-1 score, mean average precision @ 50 and @50-90. The tabulated result is shown below.

Model	**Precision**	**Recall**	**F-1**	**mAP@50**	**mAP@50-90**
M-YOLOv8	97.6	96.8	0.96	0.95	0.94
YOLOv8	96.5	95.1	0.92	0.91	0.91
R-CNN	93.8	92.1	0.91	0.90	0.90
SSD	91.2	91.7	0.89	0.89	0.88

The precision refers to how accurate the model is in identifying the croaker fish when trained in various model. The R-YOLOv8 shows a precision of 97.6 when compared with YOLOv8 of 96.5, R-CNN of 93.8 and SSD value of 91.2.

The Recall is a performance metric that measures the ability of the model to detect croaker fish The R-YOLOv8 shows a recall of 96.8 when compared with YOLOv8 of 95.1, R-CNN of 92.1 and SSD value of 91.7. The F-1 Score is a harmonic mean of Precision and Recall, giving a single metric that balances both. In this study, the R-YOLOv8 gives 0.96, while the YOLOv8 is 0.91, R-CNN is 0.91 and SSD is 0.89. this implies that the

R-YOLOv8 has a higher metric value in detecting croaker fish compared to other models. Furthermore, the mean average precision@ 50 for the R-YOLOv8 is 0.95, while the YOLOv8 is 0.91 and R-CNN is 0.90 and SSD is 0.88. this implies that the mean average precision@ 50 for R-YOLOv8 is higher compared to other models. The R-YOLOv8 shows a higher performance value in terms of precision, recall, F-1 score, mean average precision @ 50 and @ 50-90. In detecting the croaker fish in real time.

10.0: CONCLUSION

The research study indicates that the Modified YOLOv8 shows a higher performance using the accuracy, recall, precision, F-1 score, and mAP50 compared to the conventional YOLOV8, R-CNN and the SSD. The under water wireless sensory network system can be deployed in marine engineering, under water systems, aquatic environment for the detection and identification of various aquatic animals. This is expected to help consumers, pro-consumers, aquaculturist, businessmen, farmers, fisherfolks and other fishing stakeholders to be able to analyze and evaluate their prospects in the prediction of the croaker fish throughout the year. It can also help business men to predict and develop a business model in their value chain and business transactions.

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